Intelligent Perception and Situation Awareness for Automated vehicles

Christian Laugier, Julia Chartre

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ADAS & Autonomous Driving

GTC Europe 2016, Autonomous Vehicle track
Amsterdam, Sept. 28 – 29 2016

How to improve Robustness & Efficiency & Capabilities of Embedded Perception & Decision-making Systems ?

Complex Dynamic Scenes

Situation Awareness & Decision-making

Road Safety Campaign, France 2014

Anticipation & Prediction *for avoiding accidents*

Main features

- ✓ Dynamic & Open Environments => *Real-time processing*
- ✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms*
- ✓ Human in the loop => *Interaction & Social Constraints (including traffic rules)*
- ✓ Hardware / Software integration => *Satisfying Embedded constraints*

Industrial State of the Art & Today's Limitations

- **Perception** for Autonomous Vehicles: *New trend of automotive industry !*

CES 2015 & 2016
(Las Vegas)
+
Large media coverage

But perception is still a **bottleneck for Motion Autonomy**,
… in spite of significant improvements (sensors & algorithms) during the last decade

- **Robustness insufficient & High computational capabilities are required**
  Still an obstacle to the full deployment !

Trunk full of electronics & computers & processor units

Lack of Robustness & Efficiency

Lack of Integration into Embedded Sw/Hw

Numerous real-life experiments …but Safety is still insufficient

=> Some benign & serious accidents in the past few months (Google, Tesla ..)

Autonomous Car: Next generation technology & Expected market of 500 B€ in 2035

Tesla Autopilot based on Radar & Mobileye
- *Partnership with Mobileye uncertain*
- *Commercial option : 3400 € in France*

Costly 3D Lidar & Dense 3D mapping

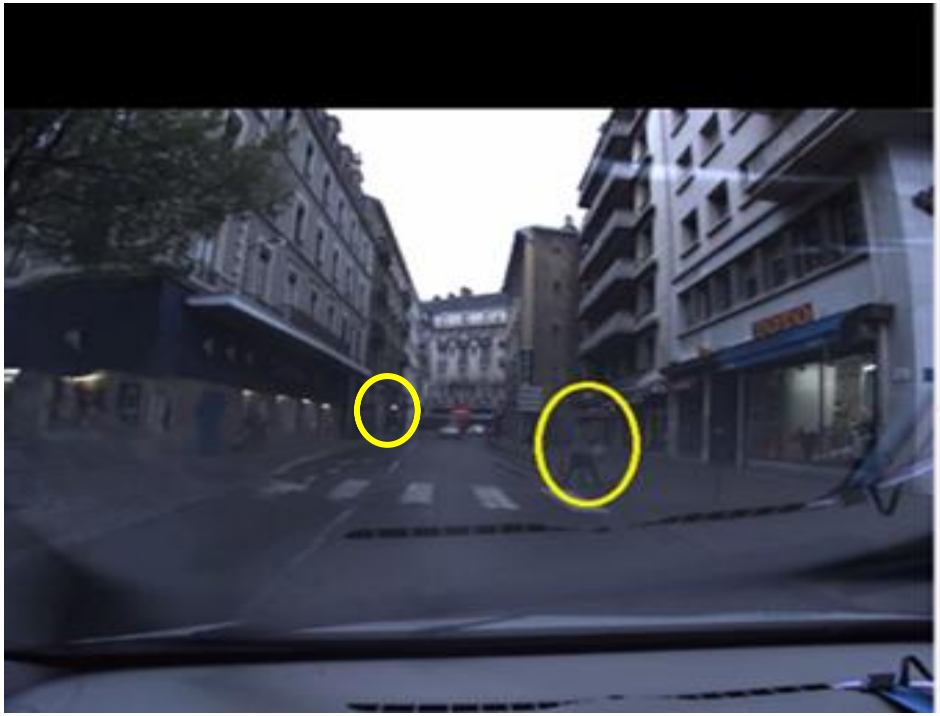
Drive Me trials
- *100 Test Vehicles in Göteborg, 80 km, 70km/h*
- *No pedestrians & Plenty of separations between lanes*

Driverless Taxi testing in Pittsburgh *(Uber)* & Singapore *(nuTonomy)*

=> Numerous Sensors & Engineer in the car during testing

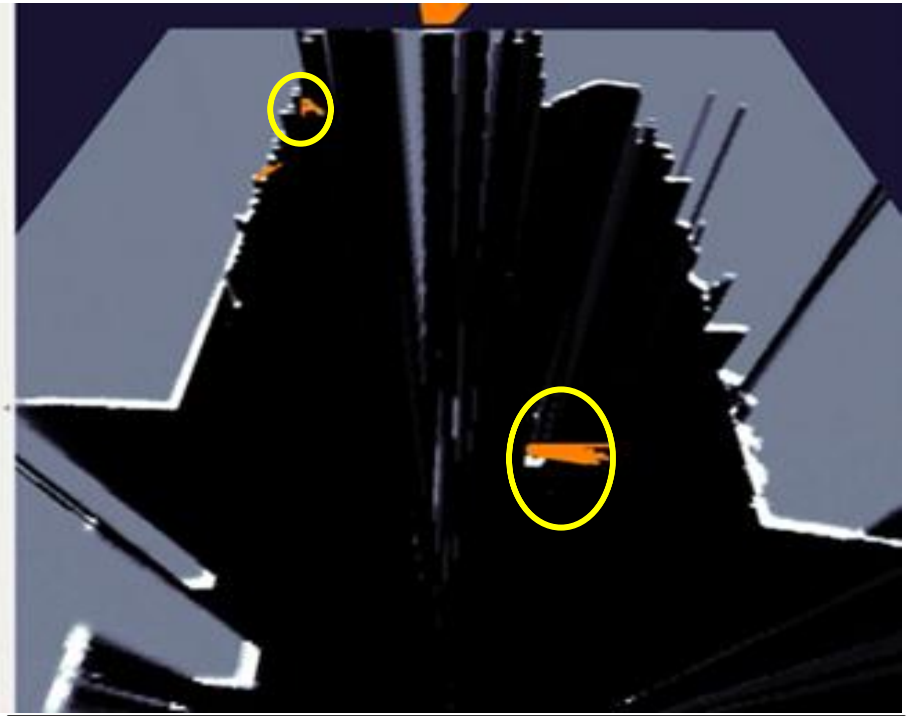
Improving robustness using Multi-modality sensing

Camera Image at Dusk *(Pedestrians not detected)*



Camera output depends on lighting conditions
Cheap & Rich information & Good for classification

Processed Lidar data *(Pedestrians detected)*



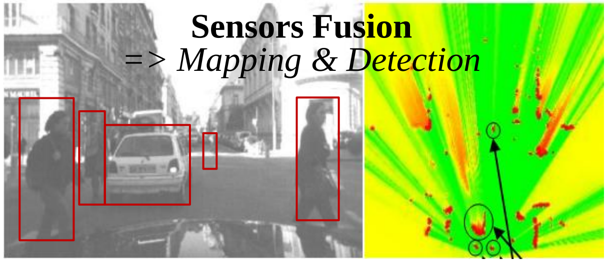
Lidar more accurate & can work at night
*Good for fine detection of objects … but **still Expensive***

- *Develop **Robust & Efficient Multi-Sensor Fusion** approaches using probabilistic models*
- ***Good news:** A new generation of **affordable "Solid State Lidars"** will arrive soon on the market !*
  => No mechanical component & Expected cost less than 1000 US$
  => Numerous announcements since Spring 2016

QUANERGY LeddarTech MASTERING LIDAR SENSOR TECHNOLOGY ZF ibeo automotive INNOVIZ TECHNOLOGIES

Key Technology 1: Embedded Bayesian Perception

Embedded Multi-Sensors Perception
⇒ Continuous monitoring of the dynamic environment



❑ Main challenges

- ✓ *Noisy data, Incompleteness, Dynamicity, Discrete measurements*
- ✓ ***Strong Embedded & Real time constraints***

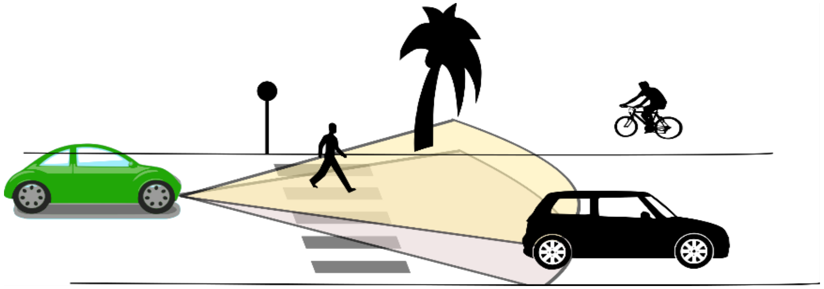
❑ Approach: Embedded Bayesian Perception

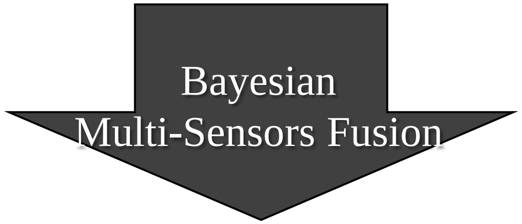
- ✓ *Reasoning about **Uncertainty** & **Time window** (Past & Future events)*
- ✓ ***Improving robustness** using **Bayesian Sensors Fusion***
- ✓ ***Interpreting the dynamic scene** using **Contextual & Semantic** information*
- ✓ ***Software & Hardware integration** using GPU, Multicore, Microcontrollers…*

Bayesian Perception : Basic idea

❑ Multi-Sensors Observations

Lidar, Radar, Stereo camera, IMU …

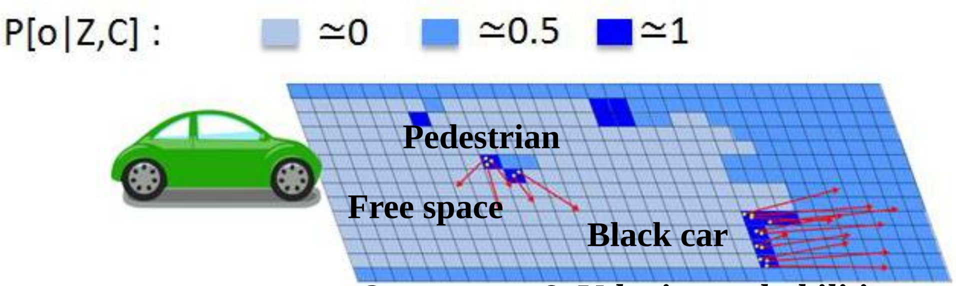




Real-time

❑ Probabilistic Environment Model

- ✓ *Sensor Fusion*
- ✓ *Occupancy grid integrating uncertainty*
- ✓ *Probabilistic representation of Velocities*
- ✓ *Prediction models*



Occupancy & Velocity probabilities
+
Embedded models for <u>Motion Prediction</u>

❑ Main philosophy

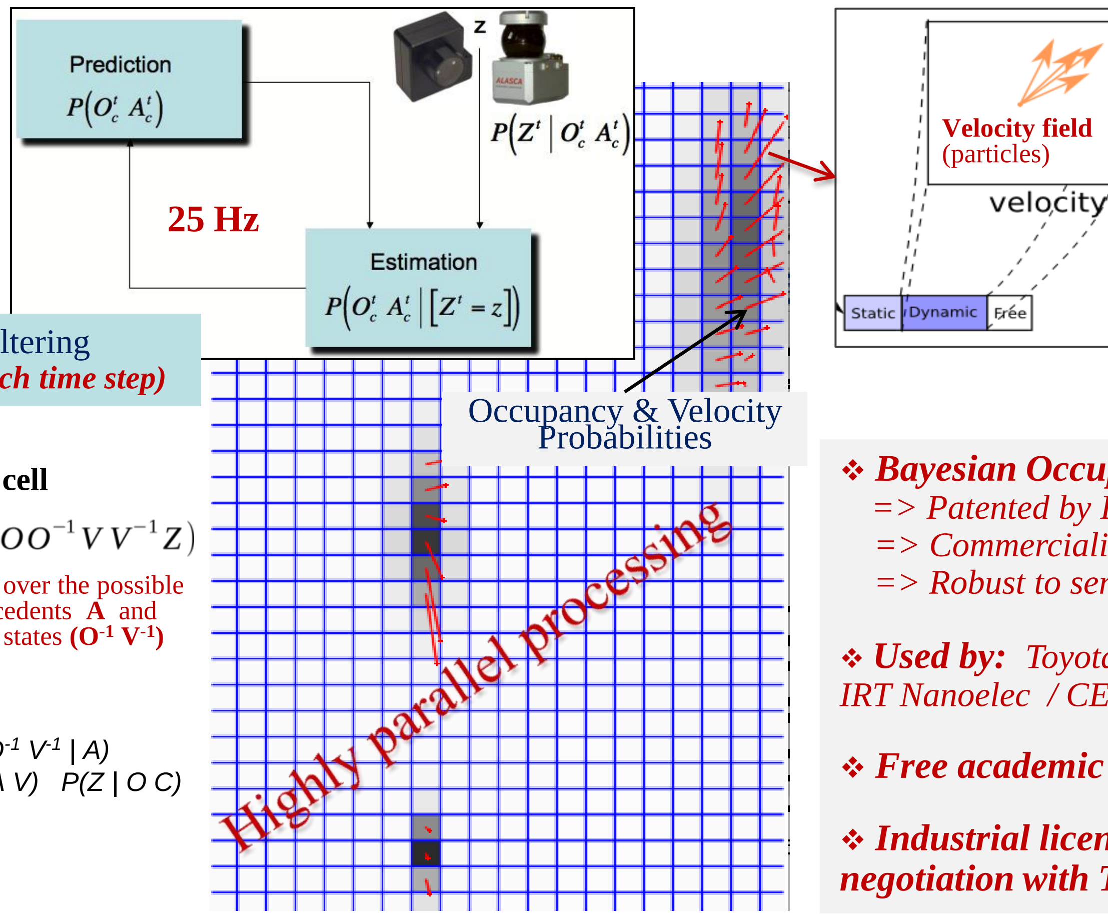
Reasoning at the grid level as far as possible for both :

- ***Improving efficiency*** *(highly parallel processing)*
- ***Avoiding traditional object level processing problems*** *(e.g. detection errors, wrong data association…)*

A new framework: *Dynamic Probabilistic Grids*
=> A clear distinction between Static & Dynamic & Free components

[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]

Sensing *(Observations)*



Bayesian Filtering
(Grid update at each time step)

Solving for each cell

$$P(O\,V \mid Z\,C) = \lambda \sum_{A\,O^{-1}\,V^{-1}} P(C\,A\,O\,O^{-1}\,V\,V^{-1}\,Z)$$

Sum over the possible antecedents **A** and their states **(O^{-1} V^{-1})**

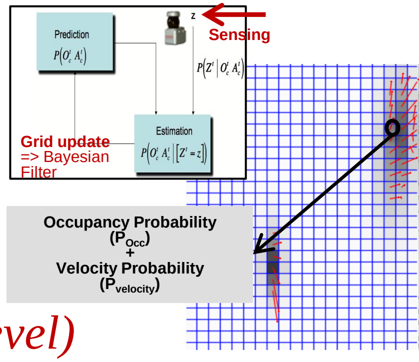
Joint Probability decomposition:

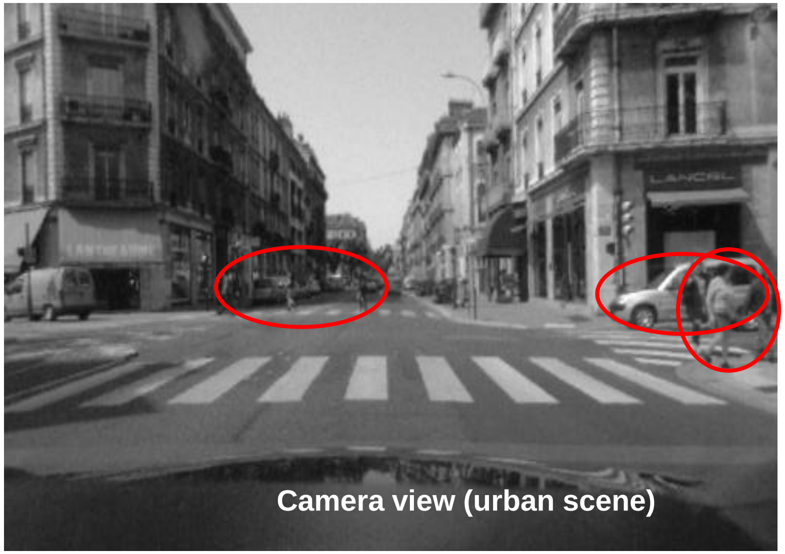
$P(C\ A\ O\ O^{-1}\ V\ V^{-1}\ Z) = P(A)\ \ P(O^{-1}\ V^{-1} \mid A)$
$\qquad P(O\ V \mid O^{-1}\ V^{-1})\ \ P(C \mid A\ V)\ \ P(Z \mid O\ C)$

- ***Bayesian Occupancy Filter (BOF)***
  => Patented by Inria & Probayes
  => Commercialized by Probayes
  => Robust to sensing errors & occultation
- ***Used by:*** *Toyota, Denso, Probayes, IRT Nanoelec / CEA*
- ***Free academic license available***
- ***Industrial license conditions under negotiation with Toyota***

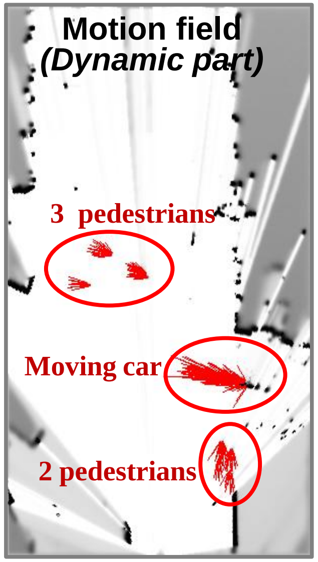
Bayesian Occupancy Filter (BOF) – *Main Features*

- Estimate **Spatial occupancy for each cell of the grid** ***P (O | Z)***
- **Grid update** is performed in <u>each cell in parallel</u> *(using BOF equations)*
- **Extract Motion Field** *(using Bayesian filtering & Fused Sensor data)*
- **Reason at the Grid level** *(i.e. no object segmentation at this reasoning level)*

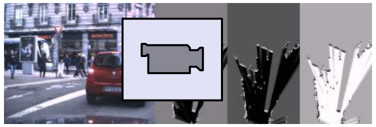




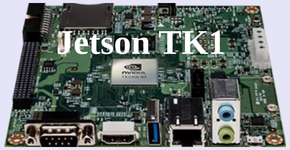
Sensors data fusion
+
Bayesian Filtering



Exploiting Dynamic information !



Recent implementations & Improvements



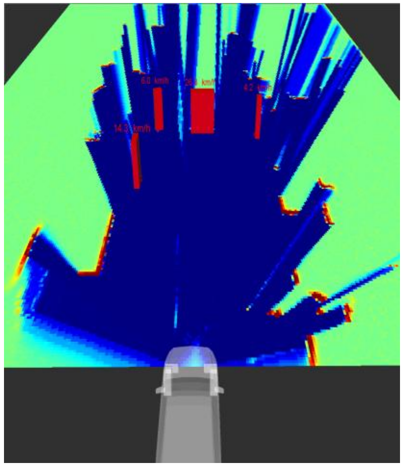
*Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity***

❖ Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014) *[Negre et al 14] [Rummelhard et al 14]*

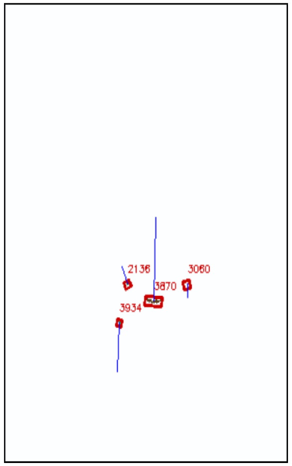
*=> Drastic **memory size reduction** (factor 100) + Increased **efficiency** (complex scenes) + More **accurate Velocity estimation** (using Particles & Motion data from ego-vehicle)*

❖ Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015) *[Rummelhard et al 15]*

*=> Increased efficiency using "state data" (Static, Dynamic, Empty, **Unknown**) + Integration of a **"Dense Occupancy Tracker"** (Object level, Using particles propagation & ID)*



Grid & Pseudo-objects



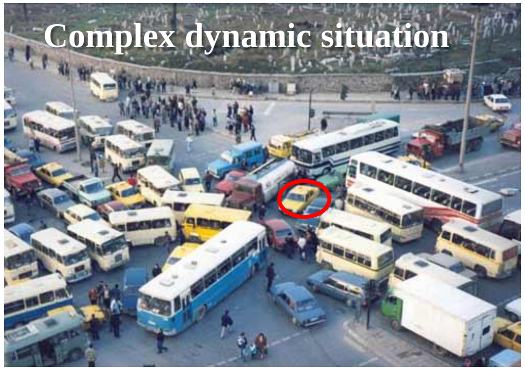
Tracked Objects

Classification *(using Deep Learning)*

Tracking & Classification
=> See experimental results at the end of the talk (video)

Key Technology 2: Risk Assessment & Decision

=> Decision-making for avoiding Pending & Future Collisions



❑ Main challenges

*Uncertainty, Partial Knowledge, World changes, **Human in the loop + Real time***

❑ Approach: Prediction + Risk Assessment + Bayesian Decision-making

- ✓ *Reason about **Uncertainty & Contextual Knowledge** (using **History** & **Prediction**)*
- ✓ ***Estimate probabilistic Collision Risk at a given time horizon*** $t+\delta$
- ✓ ***Make Driving Decisions** by taking into account the **Predicted behavior** of all the observed surrounding traffic participants (cars, cycles, pedestrians …) & **Social / Traffic rules***

Short-term collision risk – *Main features*

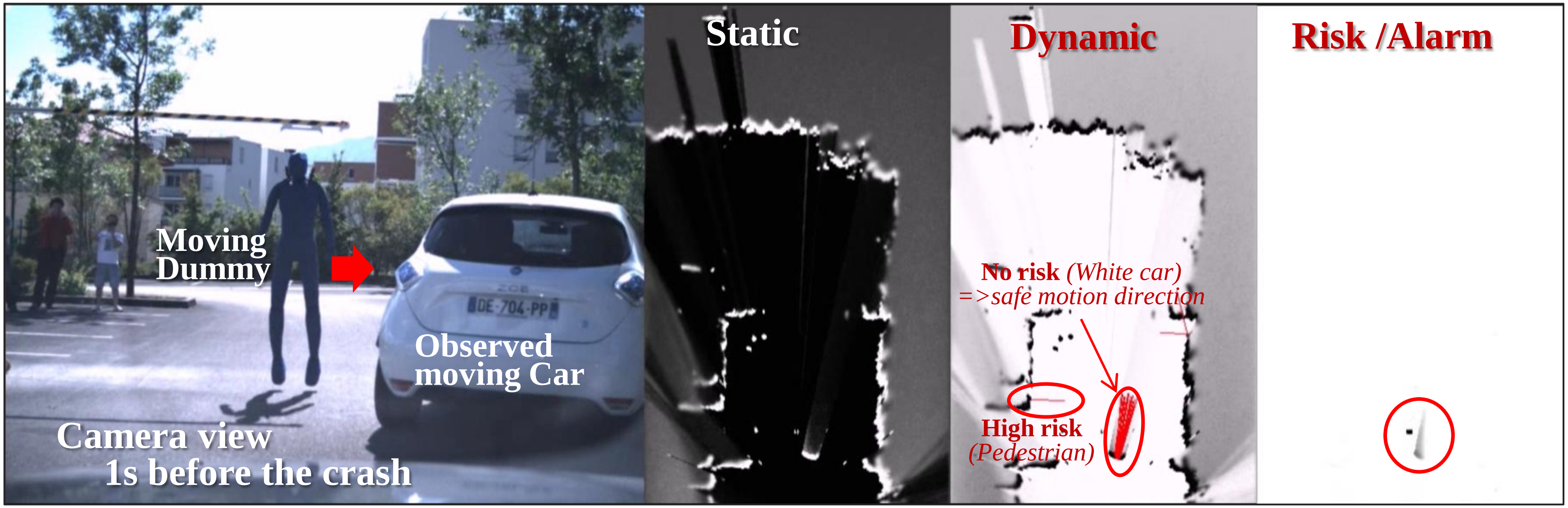
=> Grid level & Conservative motion hypotheses (proximity perception)

Proximity perception: d <100m and t <5s
δ= 0.5 s => Precrash
δ= 1 s => Collision mitigation
δ > 1.5s => Warning / Emergency Braking

Main Features

- *Detect **"Risky Situations"** a few seconds ahead (0.5 to 3s)*
- *Risky situations are **localized in Space & Time***
  - *⇒ **Conservative Motion Prediction** in the grid (Particles & Occupancy)*
  - *⇒ **Collision checking** with Car model (shape & velocity) for **every future time steps** (horizon h)*
- *Resulting information can be used for choosing **Avoidance Maneuvers***

System outputs



Short-term collision risk – *Experimental results*

Objective: ***Detect all dangerous situations & Avoid most of false alarms***

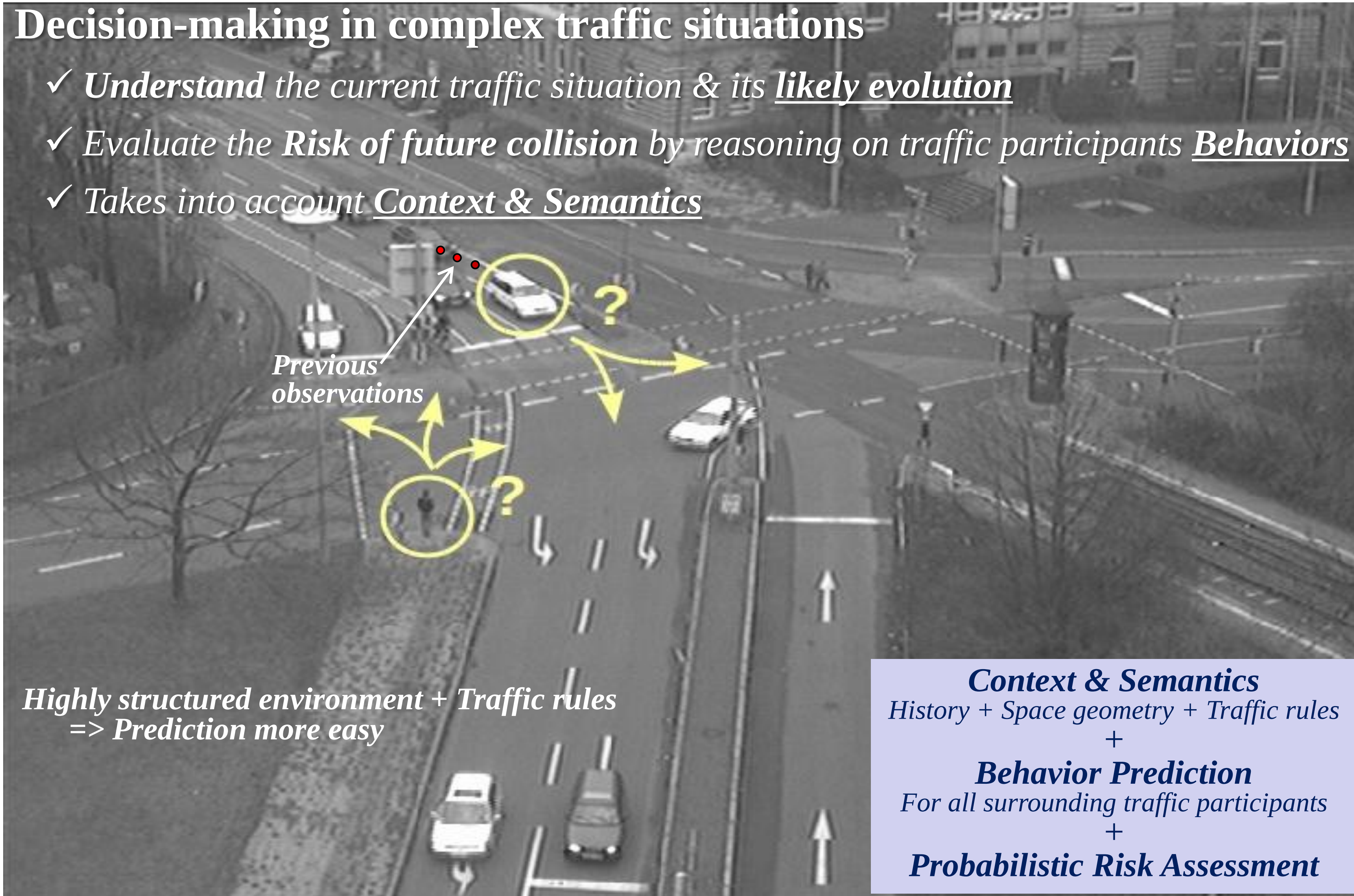
See video at the end of the talk

Generalized Risk Assessment (Object level)

=> Increasing time horizon & complexity using **context & semantics**

Decision-making in complex traffic situations

- ✓ ***Understand*** *the current traffic situation & its* ***likely evolution***
- ✓ *Evaluate the* ***Risk of future collision*** *by reasoning on traffic participants* ***Behaviors***
- ✓ *Takes into account* ***Context & Semantics***



Highly structured environment + Traffic rules
=> Prediction more easy

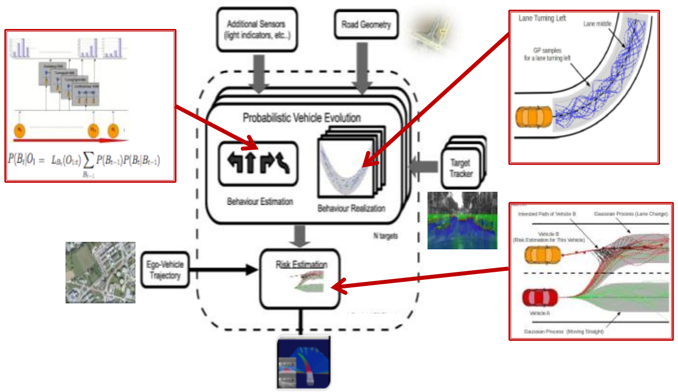
Context & Semantics
History + Space geometry + Traffic rules
+
Behavior Prediction
For all surrounding traffic participants
+
Probabilistic Risk Assessment

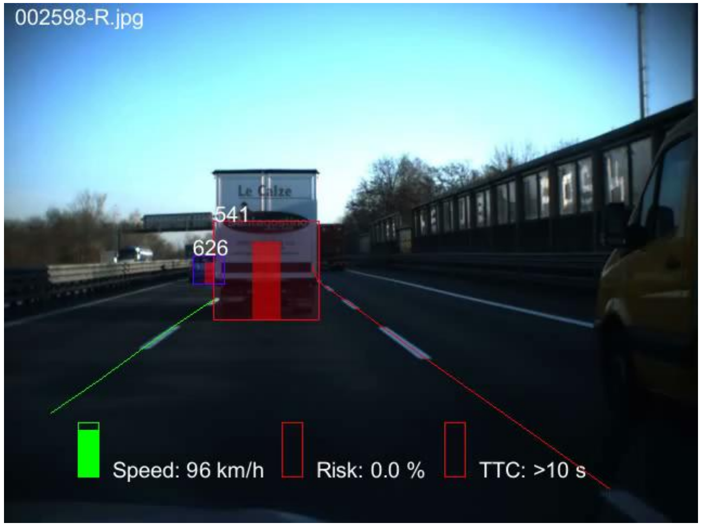
Behavior-based Collision risk *(Object level)*

=> Increased time horizon & complexity + Reasoning on Behaviors

❑ Trajectory prediction & Collision Risk

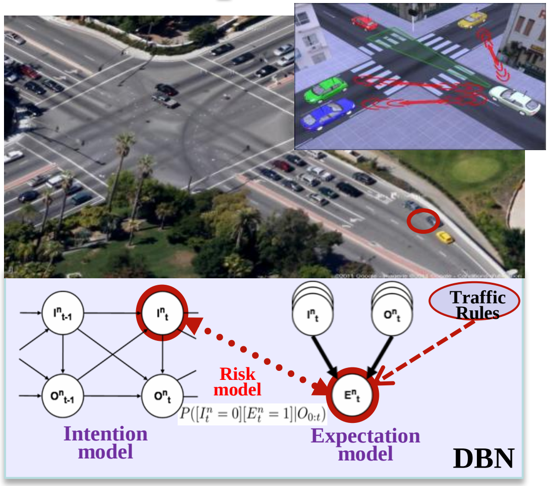
=> Patent Inria -Toyota - Probayes 2010





❑ Intention & Expectation

=> Patents Inria - Renault 2012 & Inria - Berkeley 2013



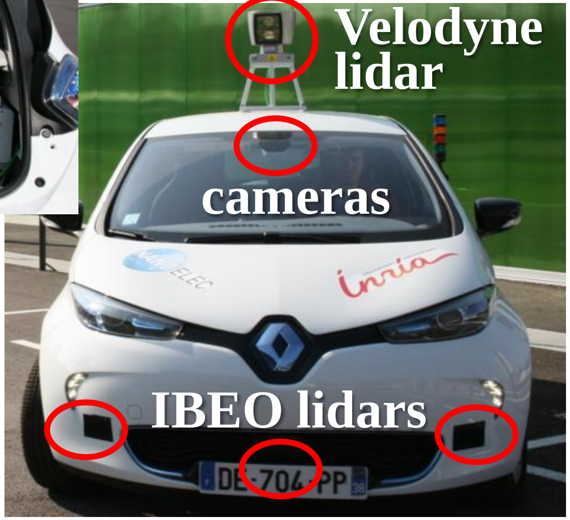
Implementation & Experimental Results

Presented by Julia Chartre

Experimental Vehicles and Perception Units

Toyota Lexus

Renault Zoé



ROS

Titan X

Jetson TK1

Jetson TX1

Perception Unit

Objectives & Achievements 2013 -17

Embedded Hardware (STHORM)

Experimental Platform

Fusion on many core architecture

Automotive Standard
Multicore.
Dual cortex A9@ 800Mhz

microcontroller

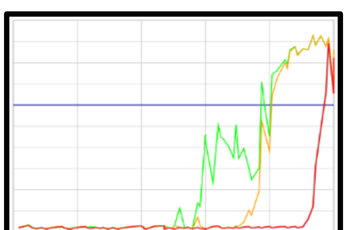
Microcontroller
STM 32 Cortex
M7@200 MHz

Nvidia Jetson Tk1

Nvidia Jetson TX1

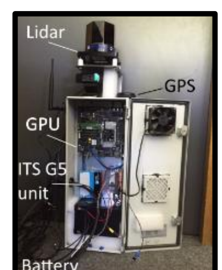
GTC Europe 2016

BOF	**HSBOF**	**CMCDOT**	**CMCDOT** *Cuda Optimization on Tegra*
2013	2014	2015	2016 - 17

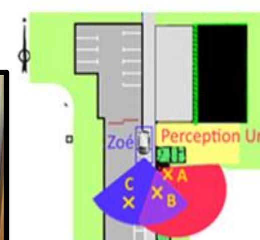


Risk assessment system

Experimental Scenario



Perception Unit

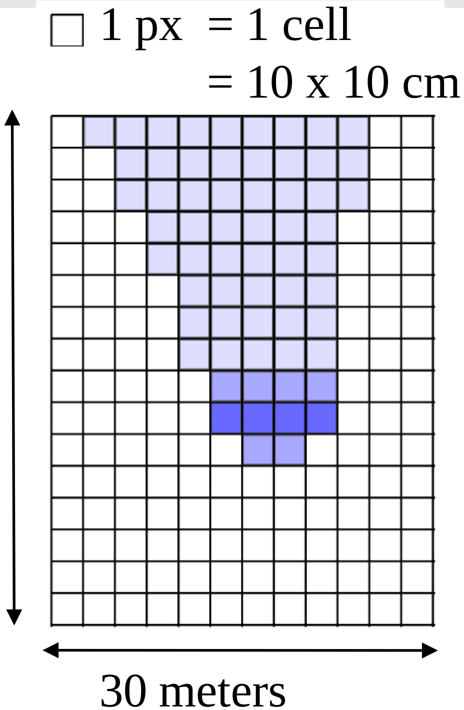


Distributed Perception

Zoe Autom. 1st Steps

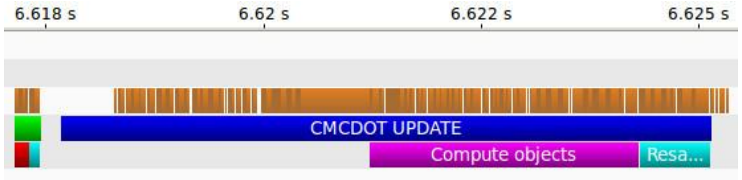
GPU Implementation

- Highly parallelizable framework, **27 kernels** over cells and particles. (Resampling, sorting, predict, occupancy, speed estimation)
- **Real-time implementation** (processing 20 Hz sensor output), optimized using Nvidia profiling tools.
    - 700 x 300 Grids
    - 32768 velocity samples
    - Configuration with **8 to 12 Lidar layers** (2x4 to 3 x 4),
- Pushing the limits of the algorithm :
    - 1400 x 600 Grids
    - 65536 velocity samples



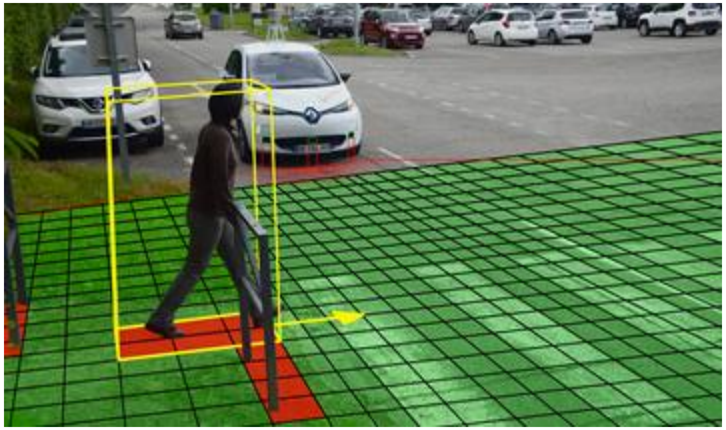
Jetson TK1: Grid Fusion 17ms, CMCDOT 70ms

Jetson TX1: Grid Fusion 0.7ms, CMCDOT 17ms

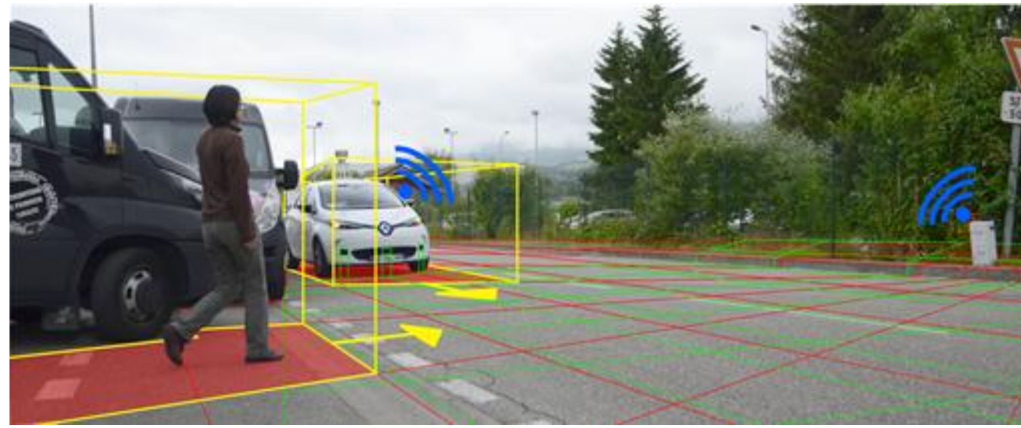


Experimental Platforms & Experiments

Embedded Perception



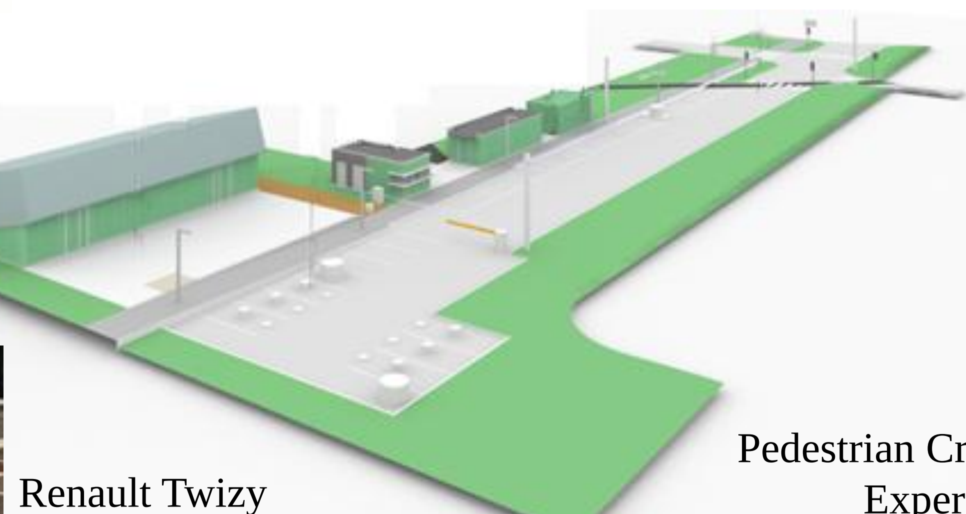
Distributed Perception



Perception Unit

Connected Traffic Cone

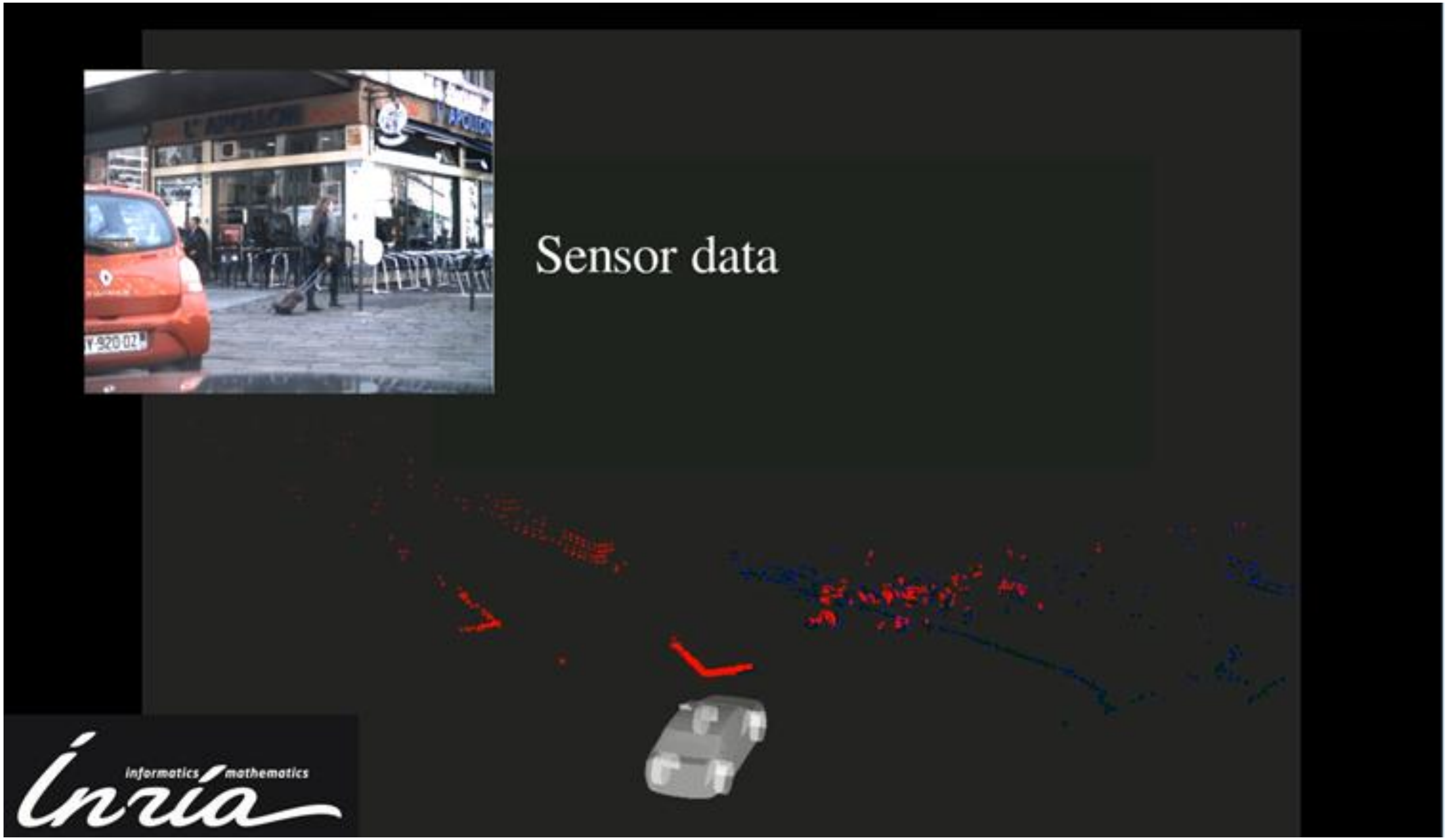
NANOELEC. IRT Nanoelec Experimental Platform

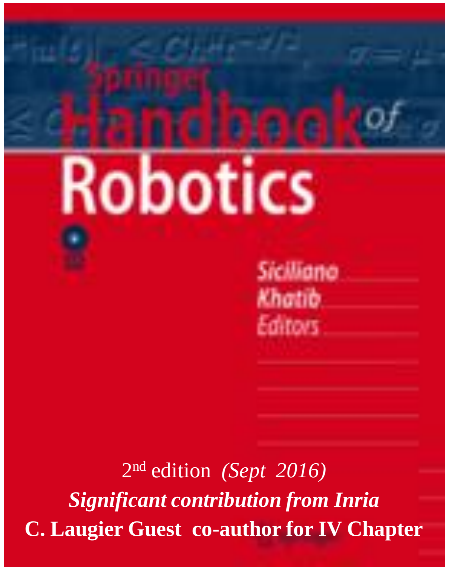


Renault Twizy

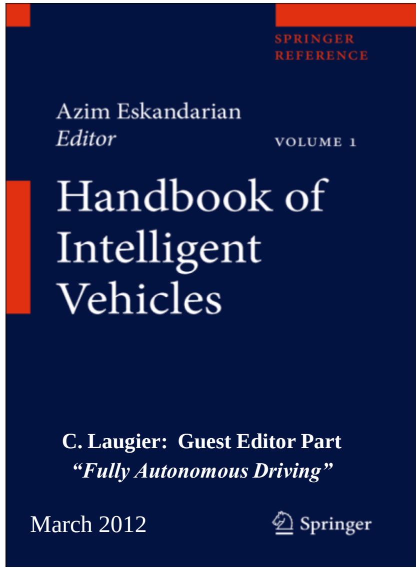
Pedestrian Crossing Experiments

Experimental results in urban environment

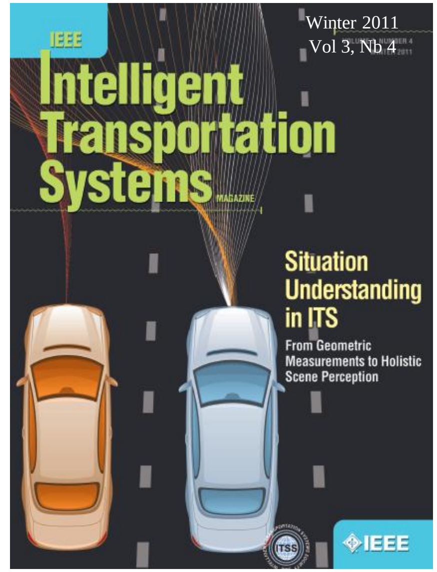




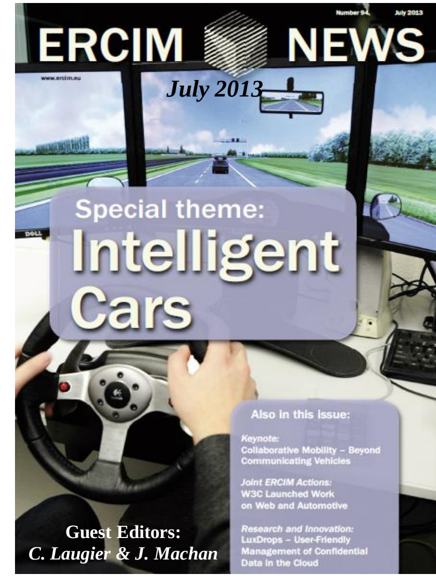
2nd edition *(Sept 2016)*
Significant contribution from Inria
C. Laugier Guest co-author for IV Chapter



C. Laugier: Guest Editor Part
"Fully Autonomous Driving"
March 2012

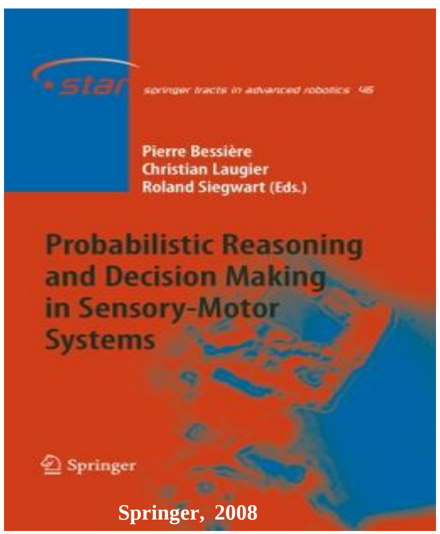


Winter 2011
Vol 3, Nb 4



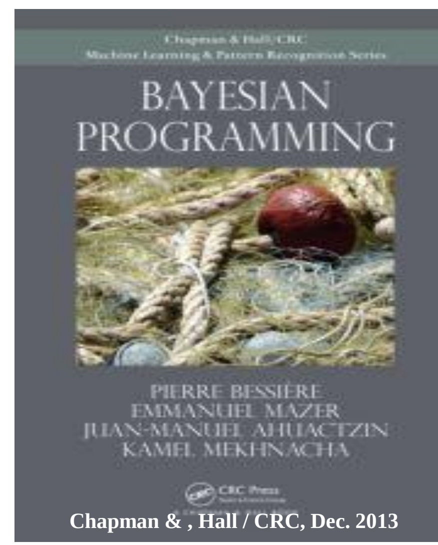
July 2013
Guest Editors:
C. Laugier & J. Machan

Thank You Any questions ?



Springer, 2008

IEEE RAS Technical Committee on "AGV & ITS"
Numerous Workshops & Special issues since 2002
=> Membership open



Chapman & , Hall / CRC, Dec. 2013